J Quant Criminol
DOI 10.1007/s10940-015-9274-5

ORIGINAL PAPER

Identifying Classes of Explanations for Crime Drop: Period and Cohort Effects for New York State

Jaeok Kim[1] · Shawn Bushway[2] · Hui-Shien Tsao[3]

© Springer Science+Business Media New York 2015

Abstract
Objective This paper advances current understanding of the contemporary crime drop by focusing on the changes in the age distribution of arrests from 1990 to 2010. Using the New York State Computerized Criminal History (CCH) file, which tracks every arrest in the state, we apply standard demographic methods to examine age-specific arrest rates over time. We test whether the 25 % drop in the felony arrest rate can be best explained by period or cohort effects with special attention to how the phenomenon varies across crime types and regions within the state.
Methods Following the analytic approach of O'Brien and Stockard (J Quant Criminol 25(1):79–101, 2009), we fit the age–period–cohort (APC) model using the generalized inverse matrix, which creates an estimable model. We partition the model variation into each factor by subtracting the variation of the two-factor model from the variation of the three-factor model to provide a direct comparison of the two different classes of explanations for crime drop: period and cohort.
Results Our analysis supports a cohort explanation over a period explanation. Controlling for the (substantial) variation due to age, the cohort effect accounts for twice as much of the remaining variation as the period effect. Specifically, the drop in arrest rates is concentrated in more recent birth cohorts across all ages. Although we found statistically significant age–period interaction effects for the younger age group (ages 16–20) in 1990

Disclaimer This data is provided by the New York State Division of Criminal Justice Services (DCJS) in the interest of information exchange. The opinions, findings, and conclusions expressed in this publication are those of the authors and not those of DCJS. Neither New York State nor DCJS assumes liability for its contents or use thereof.

✉ Jaeok Kim
jkim27@albany.edu

[1] School of Criminal Justice, University at Albany (SUNY), Albany, NY, USA

[2] University at Albany (SUNY), Albany, NY, USA

[3] Center for Social and Demographic Analysis, University at Albany (SUNY), Albany, NY, USA

Published online: 18 December 2015

and 1995, the cohort effect was still a much stronger predictor of felony arrest rates than the period explanation, even with the age–period interaction.

Conclusions The current study reports that the overall drop in felony arrest rates from 1990 to 2010 is mostly due to decreased arrests among those who were born after 1970 rather than a universal drop across different age groups. We discuss but do not test two potential explanations—the legalization of abortion and the ban on leaded gasoline—for the underlying factors associated with a different criminal propensity among birth cohorts.

Keywords Crime trend · Crime drop · Age–period–cohort model · Cohort effect · Period effect

Introduction

There have been a number of concerted efforts to explain the underlying causes of the crime drop during the last 25 years (see Arnio et al. 2012; Baumer and Wolff 2014; Levitt 2004; Rosenfeld and Messner 2009; Rosenfeld and Fornango 2014; Rosenfeld and Oliver 2008; Rosenfeld et al. 2007; Zimring 2007, 2011). However, most of the previous studies focus on testing or comparing single factors (i.e. policing strategies, abortion) that might explain the crime drop. In this article, we use the age–period–cohort (APC) modeling framework from demography to compare different classes of explanation (period vs. cohort) for the contemporary crime drop in New York State.

New York State has reported a consistent drop in the volume of index offenses over the last 20 years (NYS DCJS 2011, 2014).[1] According to the Uniform Crime Report (Federal Bureau of Investigation [FBI] 2011), there was a 60 % drop in the volume of index crime reported to the police and a 19 % decrease in the arrest volume of index offenses in New York State from 1990 to 2010. The consistent drop in the volume of crime led researchers to focus on testing period explanations for crime drop.[2] This class of explanations, such as innovative policing strategies (see Greene 1999; Weisburd et al. 2014) and increased imprisonment rates (see Marvell and Moody 1994; Levitt 1997), have generally received a great deal of attention from criminologists (O'Brien and Stockard 2009; Zimring 2011).

Cohort explanations for crime change, on the other hand, assume that social or environmental changes associated with criminal propensity affect only members of given birth cohorts during their active offending career. The relative cohort size (Easterlin 1978, 1987; Pampel and Peters 1995), the legalization of abortion (Donohue and Levitt 2001, 2004; Lott and Whitley 2007) and the banning of leaded gasoline (Reyes 2007; Stretesky and Lynch 2001) are common cohort explanations.

A casual exploration of the age-specific arrest rates in New York State during this period shows that the decrease in the arrest rates is not universal across different age

[1] Index offense refers to eight crimes that the FBI reports in the annual Uniform Crime Report (UCR): Murder, forcible rape, robbery, aggravated assault, burglary, motor vehicle theft, larceny, and arson. These crime types are selected because they are serious offenses and most likely to be reported to the police. These crimes are now referred to as Type I offenses.

[2] Demographers refer to changes that affect everyone in a given year equally, regardless of age, as period effects. Changes that affect only people from a given birth cohort regardless of age are referred to as cohort effects. Period effects may not be uniform across the entire sample. They may affect only people of a certain age (age–period interactions), or people from certain cohorts (cohort–period interactions).

groups. The younger age group (16–40 years) reported a 24 % drop in the index arrest rates, while the older age group (41–70 years) reported a 33 % increase in the index arrest rates from 1990 to 2010. This discrepancy in the temporal change of arrest rates by age group hints at the possibility of cohort explanations for the crime drop.

The demographic approach called age–period–cohort (APC) modeling can identify which class of explication (if any) can best explain the contemporary crime drop. The absence of data on age-specific crime rates forces us to change the focus from crime rates to arrest rates, which means that we are studying actions of individual offenders as well as of law enforcement officers. Only a few criminological studies (see O'Brien and Stockard 2009; Porter et al. forthcoming) have used this approach. O'Brien and Stockard (2009) estimated the APC model using the generalized inverse matrix, one of the estimable function approaches, to examine the shift in the age distribution of homicide. They found age–period interactions during the drug epidemic explained a substantial proportion of the variation across time-periods. Porter et al. (forthcoming) used the same approach to explore the changes in the age distribution of the prison population between 1974 and 2004.

In this paper, we focus on examining the extent to which period and cohort effects explain the change in the age distribution of felony arrest. Following the analytic approach of O'Brien and Stockard (2009), we estimate the three-factor (age–period–cohort) model using the generalized inverse matrix estimation and compare it with two-factor (age–period and age–cohort) models. We first compare the predicted values of the three-factor model to those of the two-factor models at a given age and period. Then, we compare the variation that is uniquely associated with period or cohort variables. Using the New York State Computerized Criminal History (CCH) analytic data file which documents all arrest events within the state between 1990 and 2010, we test whether the 25 % drop in felony arrests during this time period is explained by period changes or if certain birth cohort groups are more likely to be arrested throughout the period.

Our analysis shows that the change in the age distribution of arrests between 1990 and 2010 is more consistent with a cohort explanation than a period explanation. More specifically, the overall drop in the felony arrest rate is mostly due to the decrease in the arrest rates among birth cohorts born after 1970s, rather than period changes that effectively suppressed arrests for all age groups between 1990 and 2010. We also explore the age–period interactions (O'Brien and Stockard 2009; Zimring 2011). Although we find significant age–period interaction effects for the youngest age group (16–20 years) in 1990 and 1995, the age–period interaction only explains an additional 0.4 % of the variation in the data. The cohort effect remains a stronger predictor of arrest rates than the period effect with the age–period interaction effect.

We discuss possible cohort characteristics that might explain why the later birth cohorts (i.e. cohorts born after the early 1970s) might have lower criminal propensity than the earlier cohorts and emphasize the necessity of follow-up studies to test those characteristics. We discuss the limitations of the current study, as well as suggestions for future research, in our conclusion section.

Changes in Demography of New York State Arrestees Between 1990 and 2010

The New York State Division of Criminal Justice Services (DCJS) maintains the Computerized Criminal History (CCH) system, which is the central repository for all arrest records in New York State. The system collects demographic information for each individual arrestee as well as details of case processing such as the criminal charge for which a

person is arrested, arraigned, and disposed. Charge details include the offense class or category, the Uniform Crime Reporting (UCR) system offense category, and the New York State Penal Code (i.e. title, section, and subsection) for each arrest event. Moreover, the case records include the exact date and the region of arrest, as well as the agency that arrested the individual. Given that a change in criminal justice policy might be local for certain crime types and within geographic regions, we will explore whether the crime drop varies across crime types and regions.

New York State has experienced a large drop in the crime rate from 1990 to 2010. In 2010, there were 60.2 % fewer index crimes reported to the police than in 1990 (Federal Bureau of Investigation [FBI] 2011) despite the fact that the New York State population increased by 7.8 % during the same period (US Census Bureau 2011). This pattern repeats itself in the arrest counts, with the largest drops occurring in the most serious offenses (Appendix 1). The number of simple assault, larceny, and drug possession arrests actually increased or remained constant, suggesting that police might have directed their efforts toward minor crimes when serious offending declined (Weisburd et al. 2014; Zimring 2011, p. 125). In this paper, we will focus on the drop in arrests for felony charge offenses, regardless of crime type. Since 1990, the number of index offense arrestees decreased by 17.5 % and the number of felony arrestees decreased by 24.6 % (Table 1).

Although most of the previous research on crime trends addresses the overall drop in crime rates, the graphs of the age-arrest curves in a given year reveals another interesting and potentially important trend—the shift in the age distribution of the arrest population. This is particularly interesting since most criminologists assume that the age-crime curve is essentially constant over time and place (Farrington 1986; Hirschi and Gottfredson 1983; Steffensmeier et al. 1989; Steffensmeier and Harer 1999). In New York State, the mean age of the total arrestee population increased by 2 years from 29 to 31 between 1990 and 2010, while the mean age of index crime arrestees increased by 3 years from 27 to 30 (Table 2).

The rise in the mean age of the arrest population can be attributed to two sources: (1) the drop in the number of arrests among the younger age group (16–40 years), and (2) a consistent increase in arrest rates among the older age group (over 40 years). A visual inspection of the age-distribution of arrests in 1990 and in 2010 shows that the observed drop in felony arrests is predominantly due to the decreased arrests for the younger age group (Table 3). In fact, the number of felony arrests for those over 40 years has doubled.

Table 1 Arrest population by year and offense type

	1990	1995	2000	2005	2010	% Change 1990–2010
Total arrest	406,856	440,528	454,685	430,252	463,979	14.0
Felony	162,168	155,888	138,732	129,827	122,311	−24.6
	(39.86 %)	(35.39 %)	(30.51 %)	(30.17 %)	(26.36 %)	
Misdemeanor	244,671	284,589	315,918	300,391	341,597	39.6
	(60.14 %)	(64.60 %)	(69.48 %)	(69.82 %)	(73.62 %)	
Index Offense	121,836	115,769	98,129	92,800	100,491	−17.5
	(29.95 %)	(26.28 %)	(21.58 %)	(21.57 %)	(21.66 %)	
VFO	58,894	55,499	42,647	37,350	34,177	−42.0
	(14.48 %)	(12.60 %)	(9.38 %)	(8.68 %)	(7.37 %)	
Drug	86,181	101,676	136,550	108,189	124,099	44.0
	(21.18 %)	(23.08 %)	(30.03 %)	(25.15 %)	(26.75 %)	

VFO = Violent Felony Offense

Table 2 Summary age distribution of arrest by year and crime type

	Year	25 %	50 %	75 %	Mean	SD	N
Total arrest	1990	21	27	34	29	10.0	406,856
	1995	21	29	37	30	10.6	440,528
	2000	21	29	39	31	11.3	454,685
	2005	21	29	40	31	11.9	430,252
	2010	21	28	40	31	12.3	463,979
Misdemeanor	1990	22	28	35	30	10.4	244,671
	1995	22	30	38	31	10.8	284,589
	2000	21	30	39	31	11.4	315,918
	2005	21	29	40	32	12.0	300,391
	2010	21	28	40	31	12.4	341,597
Felony	1990	20	26	33	28	9.4	162,168
	1995	20	27	35	29	10.2	155,888
	2000	21	28	38	30	11.1	138,732
	2005	21	28	39	31	11.6	129,827
	2010	22	29	41	32	12.1	122,311
Index offense	1990	19	25	33	27	10.3	121,836
	1995	19	26	35	28	10.7	115,769
	2000	19	26	37	29	11.4	98,129
	2005	19	27	39	30	12.1	92,800
	2010	20	26	39	30	12.7	100,491
VFO	1990	19	24	31	27	9.6	58,894
	1995	19	25	33	27	10.3	55,499
	2000	19	25	35	28	10.8	42,647
	2005	19	24	35	28	11.2	37,350
	2010	19	25	35	28	11.6	34,177
Drug	1990	23	28	34	29	8.4	86,181
	1995	23	30	37	31	9.7	101,676
	2000	21	29	39	31	10.9	136,550
	2005	21	28	40	31	11.5	108,189
	2010	21	28	40	31	12.0	124,099

VFO = Violent Felony Offense

However, the share of the older age group in the total felony arrest volume at a given year was less than one-fourth of the total arrest volume.[3] If the number of arrests of those over 40 years old had not increased, the overall drop in the felony arrests would have been even more impressive 34.1 %, a full 9.5 percentage points larger than the actual drop.[4]

[3] The share of the older age group (over age 40) in the total felony arrests increases over time: 9.3 % in 1990, 13.0 % in 1995, 18.3 % in 2000, 22.1 % in 2005, and 25.3 % in 2010. Given that the total volume of felony arrests consistently decreases over time, it addresses that the drop in the felony arrest for the younger age group is large enough to compensate the increase in the older age group.

[4] The percent change in the counterfactual scenario is calculated based on assumption that the 2010 felony arrest counts for older age group has not changed since 1990: (Counterfactual arrest volume in 2010 − Actual arrest volume in 1990)/Actual Arrest volume in 1990 × 100 = (105,558–160,140)/160,140 × 100 = −34.1 %.

Table 3 Felony arrest counts and rates by age group and year

Age	Counts					% Change	Rates per 100,000					% Change
	1990	1995	2000	2005	2010	1990–2010	1990	1995	2000	2005	2010	1990–2010
16–20	41,302	37,502	31,865	28,464	23,083	−44.1	3186	3240	2466	2110	1653	−48.1
21–25	36,462	28,377	25,692	25,147	24,104	−33.9	2548	2311	2070	1898	1713	−32.8
26–30	31,675	26,619	18,972	17,887	18,657	−41.1	1986	1913	1406	1385	1356	−31.7
31–35	22,553	24,254	18,471	14,122	13,659	−39.4	1452	1544	1261	1074	1088	−25.1
36–40	13,193	17,106	17,286	14,383	11,100	−15.9	943	1139	1102	1020	868	−8.0
41–45	7093	9538	11,862	12,742	11,095	56.4	571	712	802	842	814	42.6
46–50	3817	5228	6723	8113	9544	150.0	379	448	509	569	653	72.3
51–55	1991	2717	3487	4145	5696	186.1	235	288	301	326	409	74.0
56–60	1118	1424	1784	2018	2618	134.2	138	180	197	185	217	57.2
61–65	651	712	789	980	1212	86.2	80	98	108	118	120	50.0
66–70	285	358	425	424	529	85.6	39	51	66	65	72	84.6

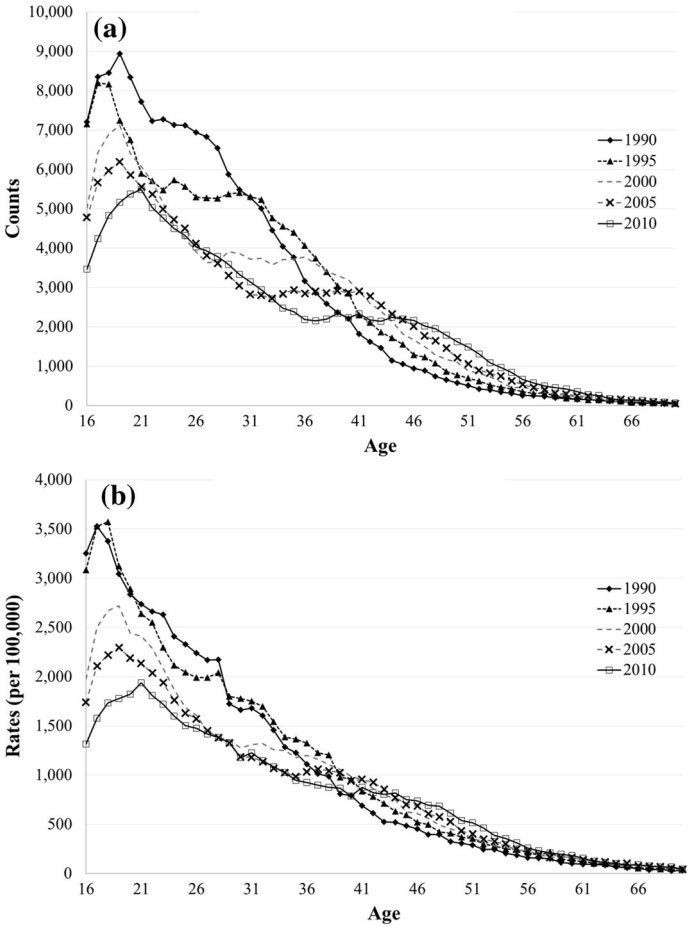

Fig. 1 Single-age distribution of felony arrest counts and rates. **a** Felony arrest counts. **b** Felony arrest rates

Between 1990 and 2010, there was a 9.2 % increase in the size of the population aged 16–70, the age group with a potential for criminal arrests. However, the population size for those aged 16–25, the age group for which criminal involvement is the highest (Gottfredson and Hirschi 1990; Snyder 2012), has increased only 2.8 % during the last 20 years. There are simply fewer younger people in 2010 relative to 1990, which is a classic cohort explanation.

Age-specific arrest rates account for changes in population composition. Although the shift in the age composition of the arrest population from 1990 through 2010 becomes less obvious, the pattern of decreased arrests among younger age groups and the reverse pattern for older age groups still remain when we shift our focus from arrest counts to arrest rates (Fig. 1 and Table 3). The graphs for the single-age distribution of arrest rates by year show that these patterns hold across most, but not all, crime types and periods (Fig. 2). For index offenses, the arrest rates among those over age 40 have increased, while the increase among the older age groups of violent felony offenses is not as clear. Although arrest rates for different types of crime, such as felony and index crime, were consistently decreasing over time, the largest drop in the arrest rates for the younger groups occurred between 1995 and 2000.

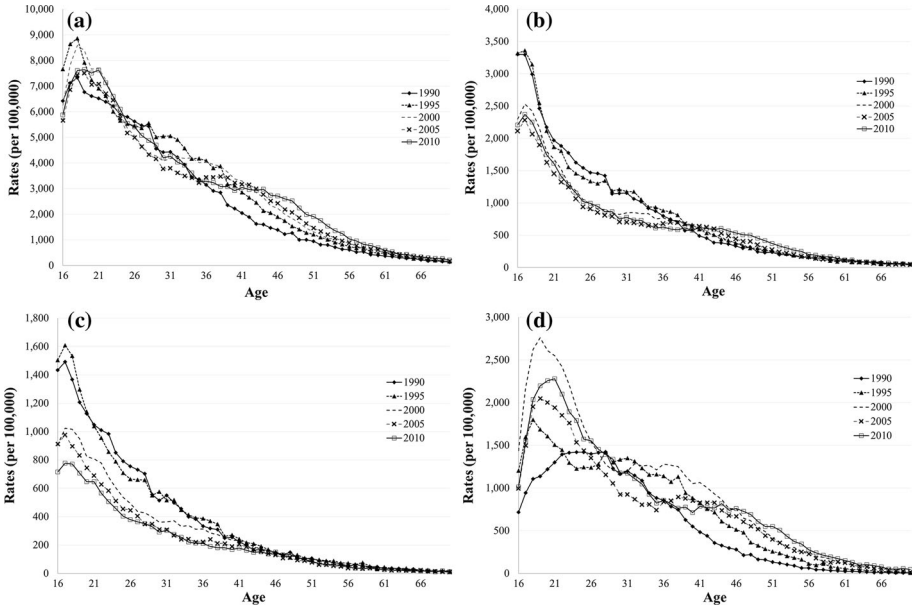

Fig. 2 Single-year age group distribution of arrest rates by crime type. **a** Total arrest rates. **b** Index offense arrest rates. **c** VFO arrest rates. **d** Drug arrest rates

In the next section, we explain our analytic strategy, which includes an estimation of the age–period–cohort (APC) model, to explore the extent to which the period or cohort differences can explain the contemporary arrest trend in New York State.

Analytic Methods

We apply an age–period–cohort (APC) analysis, a conventional demographic approach, to study the effect of period and cohort on the variation in arrest rates from 1990 to 2010 in New York State. Equation 1 represents the full model including age, period, and cohort effects.

$$Y_{ij} = \mu + \alpha_i + \pi_j + \gamma_k + \varepsilon_{ij} \quad (1)$$

where Y_{ij} refers to the estimated arrest rate of age group i at year j, μ is the intercept, α_i is the age effect of the *ith* age group, π_j is the period effect of the *jth* year, and γ_k is the cohort effect of the *kth* cohort group. The dependent variable is the felony arrest rates aggregated by age and period. We calculate age-specific arrest rates in a given year using the New York State single-age population in a given year from the US Census population estimates. We use dummy variables to code all predictors in the model.[5] We grouped five adjacent single ages into 11 groups (i.e. 16–20, 21–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, and 66–70 years). There are five periods (i.e. 1990, 1995, 2000, 2005, and 2010) and 15 birth cohort groups (i.e. 1920–1924, 1924–1929, etc.).[6]

[5] Appendix 2 shows the age groups by period and corresponding birth cohorts for our study sample.

[6] The cohort effect has a larger number of degrees of freedom than the period effect, which increases the chances of finding statistically significant non-linear effects of period and cohort. Porter et al. (forthcoming) deal with a similar problem by replacing the cohort dummy variables with a more restricted polynomial functional form, essentially restricting the degrees of freedom for both cohort and period to be the same.

Estimating age, period, and cohort effects in a single regression model creates an identification problem due to the collinearity among the three factors. If one knows two of the variables, the age and the period, the cohort is known by subtracting the age from the period (Cohort = period − age). A linear dependency between variables precludes the estimation of coefficients for age, period, and cohort effects (i.e. α_i, π_j, γ_k in Eq. 1). Applying the generalized inverse instead of the regular inverse to the least squares solution makes it possible to estimate coefficients, which are not valid for any interpretation (Scheffé 1959). Although specific coefficients in the model are not estimable, predicted values of the dependent variable in the model are still unbiased and therefore can be interpreted (Scheffé 1959; Searle 1971; Rodgers 1982). This property makes it possible to estimate the three-factor (age–period–cohort, or APC) model and compare its predicted outcomes with observed values. O'Brien and Stockard (2009) refer to this as an "estimable function approach".[7]

In this paper, we estimate: (1) the predicted arrest rates from the age–period (AP) model and (2) the predicted arrest rates from the age–cohort (AC) model, and then compare the predicted arrest rates from one of the two models to (3) the predicted arrest rates from the age–period–cohort (APC) model. By comparing the predicted values of the two-factor models and the three-factor model, we can determine whether the inclusion of the additional factor in the model generates predicted values that are closer to the observed ones. Moreover, a comparison of the sum of squares of the two-factor models and the three-factor model allows us to decompose the variation uniquely explained by each factor. For example, if we subtract the sum of squares of the AP model from that of the APC model, we can calculate how much of the model variation is uniquely associated with the non-linear effects of cohort controlling for the other two factors.[8]

Results

AP Model, AC Model, and APC Model for Arrest Rates

We start with a visual inspection of the observed values and the predicted values from the two-factor (AP and AC) models and the three-factor (APC) model. Looking at Fig. 3, the age–period–cohort model always performs better than the two-factor models regardless of the year and the age group. Between the two-factor models, the AC model reports predicted arrest rates at a given age group that are closer to the actual arrest rates than the predicted arrest rates from the AP model.

Table 4 shows the sum of squares, degrees of freedom, and F-values for age, period, cohort, and age–period interaction effects on the shift in the age distribution of felony

Footnote 6 continued
Their main finding regarding the importance of cohort effects was unchanged, despite the fact that they had far more cohorts (n = 86) in their paper. Their result shows that additional degrees of freedom does not itself lead to the conclusion that cohort explanations are more powerful.

[7] Utilizing the generalized inverse to get the estimates of the model is one of the estimable function approaches, such as the intrinsic estimator using the Moore–Penrose generalized inverse matrix. We address other types of the estimable function approach in conjunction with suggestions for future study in our discussion.

[8] Linear effects of cohort are absorbed by age and period effect, and the significant cohort effect is the non-linear effect of cohort remaining after controlling for the linear cohort effect (O'Brien, 2014a: 468–469; O'Brien and Stockard, 2009).

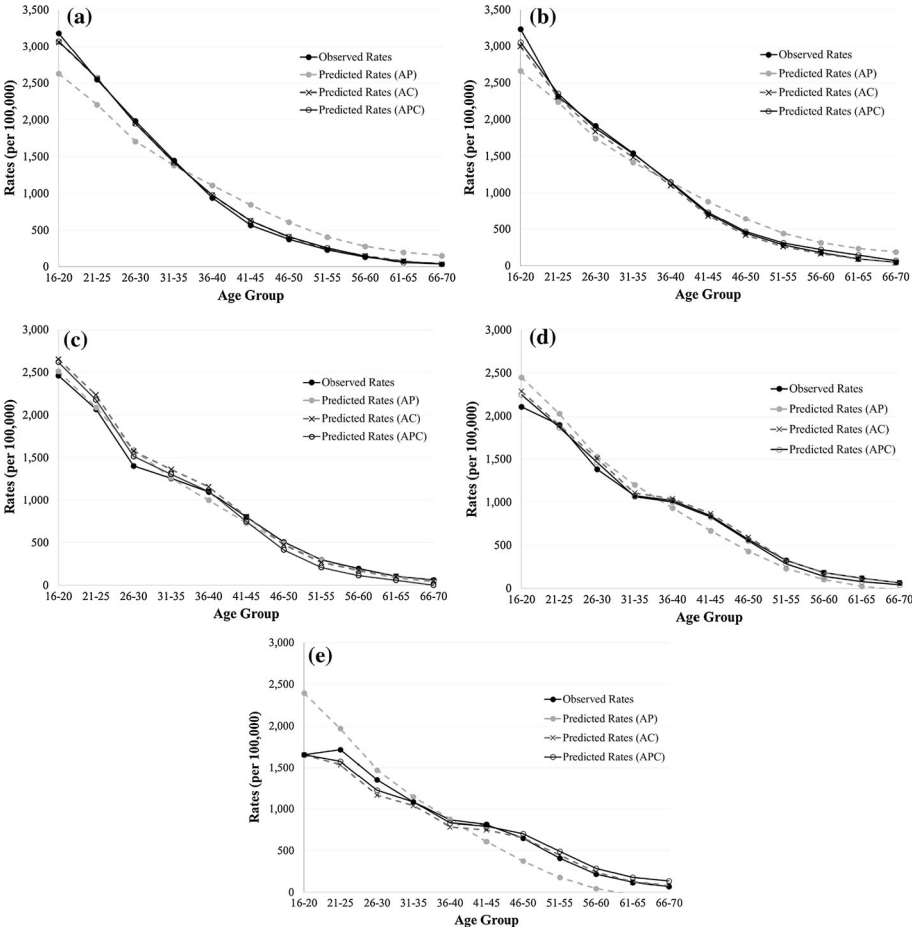

Fig. 3 Observed and predicted total felony arrest rates of the AP, AC, and APC model by year

arrest rates. Given that the sum of squares of a variable is sensitive to the order of variable input, we specifically choose the variable entry order presented in Table 4. We put the age factor in the model first so that we can estimate the effects of period and cohort while controlling for the age effect. Then we enter period dummy variables followed by cohort dummy variables in the model. This allows us to examine the extent to which the inclusion of the cohort effect improves the prediction of arrest rates after accounting for the age and period effects.

As expected, our analysis reports that age is the strongest factor in explaining variation in felony arrest rates from 1990 to 2010. Age dummies account for 92.1 % of the variability of the model (Table 4). Controlling for the age effect, period dummies account for an additional 1.5 % of the variability, while cohort dummies explain 5.8 % of the remaining variability of the model. Of the sum of squares remaining after controlling for the age effect (38,683,294–35,630,184 = 3053,110), 19.0 % (578,855/3,053,110*100) of the sum of squares is attributed to the non-linear effects of period, while 73.2 % (2,233,359/3,053,110*100) of the sum of squares is explained by the nonlinear effects of

Table 4 Summary of APC model and APC model with age–period interaction for felony arrest rates

	Age–period			Age–cohort			Age–period–cohort			Age–period–cohort interaction		
	Type I SS	df	F value	Type I SS	df	F value	Type I SS	df	F value	Type I SS	df	F value
Age	35,630,184	10	57.60***	35,630,184	10	313.13***	35,630,184	10	399.35***	35,630,184	10	1092.61***
Period	578,855	4	2.34				578,855	4	16.22***	578,855	4	44.38***
Cohort				2,711,750	14	17.02***	2,233,359	13	19.26***	2,233,359	13	52.68***
Age 16–20 * Year 1990										24,881	1	7.63*
Age 16–20 * Year 1995										134,489	1	41.24***
Error	2,474,254	40		341,359	30		240,895	27		81,525	25	
Model	36,209,039	14	41.18***	38,341,934	24	140.40***	38,442,398	27	159.58***	38,601,768	29	408.18***
Total	38,683,294	54		38,683,294	54		38,683,294	54		38,683,294	54	
% Age explained	92.1			92.1			92.1			92.1		
% Period explained	1.5						1.5			1.5		
% Cohort explained				7.0			5.8			5.8		
% Age*Period interaction										0.4		
R-square	0.936			0.991			0.994			0.998		

* $p < .05$; ** $p < .01$; *** $p < .001$

cohort. The results of the model for index arrest is similar to those of the model for felony arrest. The sum of squares explained by the non-linear effects of cohort (59.8 %) is twice as large as the sum of squares explained by the non-linear effects of period (25.0 %).[9]

We also estimated the APC model by different crime types (e.g., violent felony arrests and drug arrests). Among all models of crime type, the age factor accounts for most of the variability (90–98 %) in arrest rates during this period. In other words, the age-crime distribution captures most of the variation observed in the data. However, period and cohort effects are still statistically significant after controlling for age (tables and graphs not shown).[10] Of the two effects, the cohort effect explains more of the variation than the period effect for most of the models. In all five models by crime type, the period effect explains 19.0–39.0 % of the remaining variability. On the other hand, the cohort effect explains 53.0–88.8 % of the remaining variability.

How Much of the Drop in the Felony Arrest is Explained by Period and Cohort?

In this paper, we are particularly interested in estimating the extent to which the AP model and the AC model explain the decrease in arrest rates. In the earlier section describing the change in arrests, it appeared that the drop in the arrests over time was apparent only in the younger age group (16–40 years). Although the arrest rates for the older groups (over 40 years) showed a consistent increase, the increased arrest rates for the older group did not cancel out the drops in the young cohorts due to the relatively small number of arrests involving older individuals.

We attempt to estimate the extent to which the period effect predicts the arrest counts, as opposed to the cohort effect, by comparing the overall amount of crime drop estimated from two-factor models (AP and AC) to the actual volume of the crime drop for those between ages 16 and 39. As before, we fit the AP model and AC model using single-age, period, and cohort dummy variables. Figure 4 shows the age distribution of observed felony arrest counts in 1990 and 2010, as well as the predicted felony arrests at a given age in 1990 and 2010 estimated from the AP model (left) and the AC model (right).

Figure 4 demonstrates that the AC model better fits the observed felony arrest counts at all age groups. Among those aged 16–39, there were 54,605 fewer felony arrests in 2010 compared to 1990. We calculate how much of the crime drop in this age group can be estimated from the AP model by getting the differences from the predicted counts in each age between two periods. We did the same calculation to get the amount of the arrest reduction estimated from the AC model. While the AP model explains 39.1 % of the crime drop (=21,347.7/54,605), the AC model explains 89.2 % of the crime drop in that age group (=48,725.1/54,605). Not only does the cohort model better capture the changes in overall distribution, it also better explains the drop in arrests between 1990 and 2010.

[9] The results table and figure are not included in this paper but available upon request.

[10] Although the coefficients in the age–period–cohort model are not estimable (and therefore not available for statistical testing), the coefficients in the two-factor (AP and AC) models are still estimable and available for hypothesis testing.

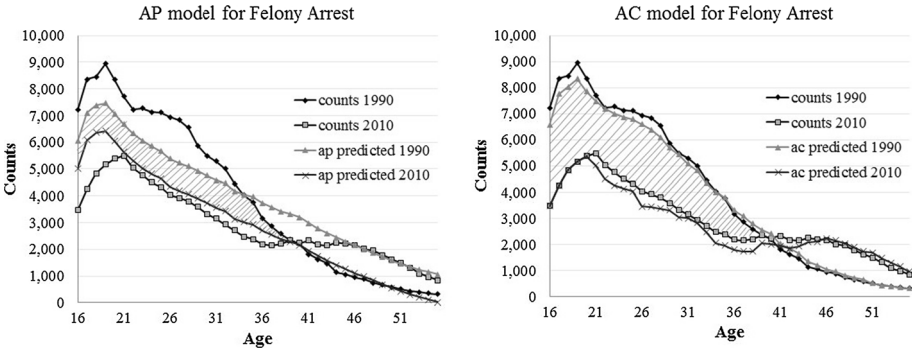

Fig. 4 Comparison between the observed values and the predicted values from the AP and AC model

Age–Period Interaction Versus Cohort Effect

The predicted values of the APC model for each age and year at arrest are similar to the actual arrest rates with small deviations (Fig. 3). One distinct pattern that emerged from the comparison of the AP, AC, and APC models is that the AP model routinely creates the worst fit among the three models. However, there appears to be period effects for certain age groups. For example, there is an upturn of arrest rates in the youngest age group (16–20 years) in 1990, 1995, 2000, and 2010. This pattern holds throughout the models for different crime types, such as index offenses and violent felony offenses. Therefore, it is at least possible that age–period interactions will better describe or account for some of the non-linear effect attributed to cohort in the previous model.

We initially estimated the AP model with one additional interaction term at a time. The age–period interaction terms of the younger age groups (16–20 and 21–25 years) were almost always significant. We then estimated the model with two interaction terms that were significant in the previous step. We ran the model for all arrests and separately by crime type to see if there is any general pattern across crime type. The model with interaction terms for ages 16–20 and 1990 and 1995 had the highest R-square. However, these two interaction terms account for only an additional 0.4 % variation of the model (Table 4). Given that the age–period interaction does not explain much of the remaining variation, we argue that the age–period interactions do not replace or account for the observed cohort effects in the model.[11]

Regional Differences in the Age Distribution of Arrest

One way to make further progress in understanding the potential source of the cohort effect is to explore regional differences in the changes in the arrest distribution. Thus, we estimated the models separately by region: NYC, IMPACT, and upstate counties. In 2004, New York State public safety officials identified 17 cities that generated 80 % of the index arrests outside of NYC and gave special attention to these "Operation IMPACT" counties. These counties include the major urban areas of Buffalo, Binghamton, Syracuse, Utica,

[11] We also checked the graphs for the model including age*period interaction and confirmed that it does not do any better job than the age–period model.

Rochester and Albany.[12] The term upstate counties refer to the remaining counties excluding NYC and the IMPACT counties.

Our exploration of the arrest rates in each age group by the three different regional categories confirms the universality of the change in the age-arrest distribution. Counties with higher crime rates tend to report similar patterns of change in arrest. Both NYC counties and IMPACT counties report greater drop in the arrest rates during this period (−43.7 % for NYC counties; −27.4 % for IMPACT counties). These counties report a greater drop in arrest rates among those under age 40.[13] Felony arrests in the more rural upstate counties actually increased by 15.7 %, with increases in every age group except the youngest age group (15–19 years). However, felony arrests among younger age groups increased at less than half the rate of older age groups.

One specific period effect to consider is the crack epidemic that had swept the large cities in New York State. In all New York State regions, a noticeable upturn in arrest rates for adolescents and young adults (15–24 years) in 1990 and 1995 is consistent with the description from the previous studies on the disproportionate impact of the crack epidemic on the younger population (see O'Brien and Stockard 2009; Zimring 2012). Despite this fact, the main conclusion from the regional comparison is the importance of the cohort in explaining the arrest trend in both NYC and IMPACT counties. In NYC counties, birth cohorts born between 1956 and 1965 reported consistently higher rates of arrest than the other birth cohorts at the same age. Except for 1990, felony arrest rates for those born between 1956 and 1965 were higher than the arrest rates of the other birth cohorts at a given age. For example, higher arrest rates of the ages 30–34 and 35–39 groups were clear in the 1995 age distribution, which is somewhat unconventional given that the traditional arrest rates show a monotonic decrease after the peak age. In 2000, the ages 35–39 and 40–44 groups, which are the same cohorts as the ages 30–34 and 35–39 groups in 1995, reported an upturn in arrest rates. The arrest rates for these birth cohorts remained high throughout their lifetime, even in their 40 s (in 2010). The same pattern is apparent, albeit to a slightly lesser extent, in IMPACT counties, but it appears largely absent in the more rural upstate counties.[14]

Next, we estimate the age–period–cohort model for total arrest rates and different types of crimes to explore regional variation on the effects of the period and the cohort. In the models for upstate counties, the age factor explains most of the total sum of squares (96.0–98.9 %), while both period and cohort factors explain less than 3.0 % of the variability after accounting for the age effect. In the models for NYC and IMPACT counties, period and cohort effects play a substantial role even after controlling for the age effect. The cohort effect is largely an urban phenomenon that needs further exploration.

[12] The 17 IMPACT counties are: Albany, Broom, Chautauqua, Dutchess, Erie, Monroe, Nassau, Niagara, Oneida, Onondaga, Orange, Rensselaer, Rockland, Schenectady, Suffolk, Ulster, and Westchester; Project IMPACT has been replaced with operation Gun Involved Violence Elimination (GIVE), which remains focused the same 17 counties, but has evolved to focus specifically on gun violence.

[13] Single-age population information at the county level is not available in the Census data. We used new age groups following the grouping of the Census for the APC analysis by region. The new age groups are as follows: 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, and 65–69 years.

[14] The felony arrest rates in the rural upstate counties actually increased for the last 20 years. However, the magnitude of increase for the younger age group is much smaller than that for the older age group, which is in accordance with cohort explanation.

Discussion and Conclusion

This paper contributes to our understanding of contemporary crime drop using the age–period–cohort model from demography. We apply an estimable function approach to test different classes of explanations (period and cohort effects) for crime trend. Given that most of the previous studies on crime trends focus on a single class of the explanation (period effect), our study fills the gap in the literature by providing a novel approach to compare two distinct classes of explanations for the crime trend in New York State.

In this study, we are particularly interested in understanding the recent (1990–2010) crime drop as reflected in arrests for felony and index arrests in New York State.[15] Our main conclusion is that cohort changes can best explain the observed drop in the arrest rate. To put it another way, the arrest rates for cohorts born after the early 1970s are consistently lower than the arrest rates for cohorts born before the 1970s across all ages. Some, but not all, of that cohort effect can be attributed to the decrease in the size of these post baby-boom cohorts.

We also find statistically significant age–period interaction effects in the youngest age group (16–20 years) in 1990 and 1995. This might be a carry-over effect of the crack epidemic from the 1980s. Previous literature has consistently reported that the crack epidemic disproportionately influenced younger age groups. The higher homicide rate of this age group is evidence for this argument (see O'Brien and Stockard 2009; Zimring 2012). However, our study suggest that the cohort model explains more of the changes in the felony arrest rates than the period model even with these age–period interactions. We also showed that cohort effects are apparent in most other crime types and in urban New York State counties (i.e., Operation IMPACT counties) as well as New York City, but not for rural upstate counties, where there is little evidence of any cohort or period effect. The universality of our findings across urban regions suggests that New York City-centric explanations such as innovative policing strategies may not be appropriate when describing the overall crime drop in New York State. More generally, our results support explanations of the crime drop that focus on changes that are isolated in the youngest cohorts. Indeed, our results show clearly that the oldest cohorts (those over age 40) actually experienced an increase in arrest during this period. If this had not occurred, the observed drop in arrests would actually have been 40 % larger.

One promising area of future study involves exploring specific explanations for the cohort effect. The existing literature on cohort effects proposes two potential explanations that occurred in the 1970s: the legalization of abortion and the ban on leaded gasoline. Previous research on the legalization of abortion suggests that the social change after the civil rights movement might have disproportionately affected the births of those who had a higher risk of criminal involvement (Donohue and Levitt 2001, 2004). Controversially, Donohue and Levitt (2001) suggested that the parents of "unplanned" children might be less able to provide an appropriate environment for their children, which might increase health risks and criminal involvement among those children. According to this argument, legalization of abortion decreases the number of "unplanned" births that are under the "suboptimal conditions" of living (Donohue and Levitt 2001) by giving those parents an alternative option. Meanwhile, scientific evidence of the harmful effect of long-term lead

[15] We explored the correlation between the number of index crimes reported to the police and the number of index arrests in a given year in New York State between 1990 and 2010. The correlation between the volume of index offenses reported to police and the volume of index arrests is very high ($r = 0.931$–0.960) across years.

exposure on human health ((Dietrich et al. 2001; Moffitt and Silva 1988; Needleman et al. 1996) eventually led to legislation banning the use of lead-based paints in the walls, door, windows, and sills of all housing and eliminating leaded gasoline in cars. Although the link between lead exposure and crime is controversial, several previous empirical studies have found relatively strong evidence supporting this relationship (Needleman 2000; Nevin 2000; Reyes 2007). Unfortunately, the CCH data do not contain any information that would allow us to test the abortion or leaded gasoline hypothesis more closely. Other data sources that include measures of criminal propensity would be useful for further exploration of this topic. For example, Porter et al. (forthcoming) explored the changes in the distribution of the prison population using an inmate survey that includes self-reports of drug abuse behavior along with numerous other measures of criminal propensity.

Previous studies (O'Brien 2000; O'Brien and Stockard 2009) using the APC analysis tried to resolve the identification issue in the age–period–cohort model by replacing a cohort variable with a proxy that represents cohort characteristics. Following this approach, one can examine whether given cohort characteristics can be significant predictors of the change in the crime rate after controlling for the covariates. In addition, future studies that explore the factor(s) affecting differential criminal propensity by cohort should consider exploiting regional differences in the crime drop. Factors affecting criminality of cohorts might have been implemented at different times, and to different extent, across regions. Although these approaches would not test the causal link between a specific cohort characteristic and crime, it should narrow and guide future work on the types of plausible cohort explanations for the crime drop.

More broadly, we believe that future criminological research on the change in crime rates can benefit from the estimable function approach that compares the variation uniquely explained by the variable of interest to the variation explained by the rest of the predictor variables (O'Brien and Stockard 2009). Along with the estimable function approach used in our study, criminological and criminal justice studies can benefit from other estimable function approaches such as the traditional method of placing a constraint on a variable (O'Brien 2014b), as well as the recently introduced intrinsic estimator (IE) method (Fu 2000).[16] For example, by placing constraints on predictor variables, it is possible to test changes in slopes within a given factor (O'Brien 2014a; Tarone and Chu 1996). In the current study, we find that the cohorts born in later years (i.e. around early 1970s) are less likely to be arrested for felony offenses, but did not test when exactly this change in the criminal propensity among birth cohorts occurred. Future research might examine the timing of change more specifically by putting constraints on the cohort variable. Future research incorporating different estimable function approaches might also shed light on the exact nature of the cohort changes observed in this study.

Acknowledgments The authors wish to acknowledge the feedback from the National Academy of Sciences Roundtable on Crime Trends. In particular, we wish to thank Richard Rosenfeld and Malay Majmundar for support and encouragement. We also wish to think the New York State Division of Criminal Justice Services, which provided access to the Computerized Criminal History File. Finally, the Center for Social and Demographic Analysis of the University at Albany provided technical and administrative support for this research through a grant from the National Institute of Child Health and Human Development (R24-HD044943).

[16] Intrinsic Estimator method(IE) also provides estimable functions, but is less sensitive to the selection of linear constraints (Yang et al. 2004; Yang et al. 2008).

Appendix 1

See Fig. 5.

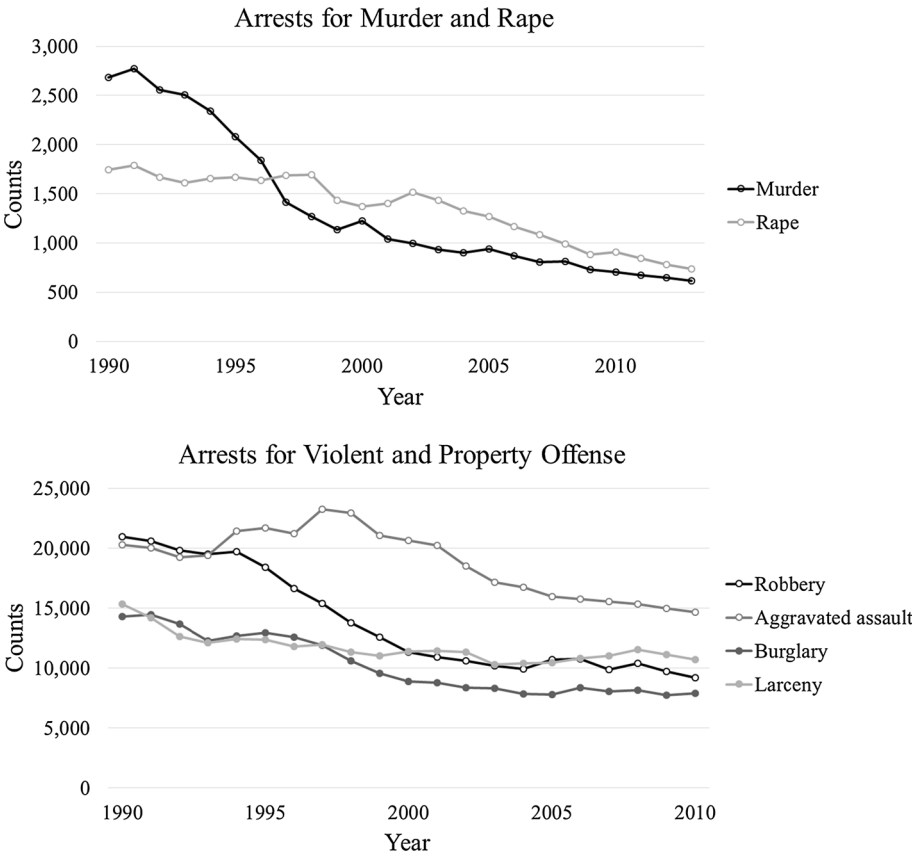

Fig. 5 Felony arrest trends by offense type

Appendix 2

See Table 5.

Table 5 Age group, period, and cohort group of the study

Age	Period				
	1990	1995	2000	2005	2010
16–20	1974–1970	1979–1975	1984–1980	1989–1985	1994–1990
21–25	1969–1965	1974–1970	1979–1975	1984–1980	1989–1985
26–30	1964–1960	1969–1965	1974–1970	1979–1975	1984–1980
31–35	1959–1955	1964–1960	1969–1965	1974–1970	1979–1975
36–40	1954–1950	1959–1955	1964–1960	1969–1965	1974–1970
41–45	1949–1945	1954–1950	1959–1955	1964–1960	1969–1965
46–50	1944–1940	1949–1945	1954–1950	1959–1955	1964–1960
51–55	1939–1935	1944–1940	1949–1945	1954–1950	1959–1955
56–60	1934–1930	1939–1935	1944–1940	1949–1945	1954–1950
61–65	1929–1925	1934–1930	1939–1935	1944–1940	1949–1945
66–70	1924–1920	1929–1925	1934–1930	1939–1935	1944–1940

Birth cohorts are represented in the diagonals (from upper left to lower right) of the table

References

Arnio AN, Baumer EP, Wolff KT (2012) The contemporary foreclosure crisis and US crime rates. Soc Sci Res 41(6):1598–1614. doi:10.1016/j.ssresearch.2012.05.013

Baumer EP, Wolff KT (2014) Evaluating contemporary crime drop(s) in America, New York City, and many other places. Justice Q 31(1):5–38. doi:10.1080/07418825.2012.742127

Dietrich KN, Douglas RM, Succop PA, Berger OG, Bornschein RL (2001) Early exposure to lead and juvenile delinquency. Neurotoxicol Teratol 23(6):511–518. doi:10.1016/S0892-0362(01)00184-2

Donohue JJ III, Levitt SD (2001) The impact of legalized abortion on crime. Q J Econ 116(2):379–420. doi:10.2307/2696468

Donohue JJ III, Levitt SD (2004) Further evidence that legalized abortion lowered crime: a reply to Joyce. J Hum Resour 39(1):29–49. doi:10.2307/3559004

Easterlin RA (1978) What will 1984 be like? Socioeconomic implications of recent twists in age structure. Demography 15(4):397–432. doi:10.2307/2061197

Easterlin RA (1987) The new age structure of poverty in America: permanent or transient? Popul Dev Rev 13(2):195–208

Farrington DP (1986) Age and crime. Crime Justice 7:189–250. doi:10.2307/1147518

Fu WJ (2000) Ridge estimator in singulah oesiun with application to age–period–cohort analysis of disease rates. Commun Stat Theory Methods 29(2):263–278

Gottfredson M, Hirschi T (1990) A General theory of crime. Stanford University Press, Stanford

Greene JA (1999) Zero tolerance: a case study of police policies and practices in New York City. Crime Delinq 45(2):171–187. doi:10.1177/0011128799045002001

Hirschi T, Gottfredson M (1983) Age and the explanation of crime. Am J Sociol 89(3):552–584. doi:10.1086/227905

Levitt SD (1997) Using electoral cycles in police hiring to estimate the effect of police on crime. Am Econ Rev 87(3):270–290

Levitt SD (2004) Understanding why crime fell in the 1990s: four factors that explain the decline and six that do not. J Econ Perspect 18(1):163–190. doi:10.1257/089533004773563485

Lott JR, Whitley J (2007) Abortion and crime: unwanted children and out-of-wedlock births. Econ Inq 45(2):304–324. doi:10.1111/j.1465-7295.2006.00040.x

Marvell TB, Moody CEJ (1994) Prison population growth and crime reduction. J Quant Criminol 10(2):109–140. doi:10.1007/BF02221155

Moffitt T, Silva P (1988) Self-reported delinquency, neuropsychological deficit, and history of attention deficit disorder. J Abnorm Child Psychol 16(5):553–569. doi:10.1007/BF00914266

Needleman HL (2000) The removal of lead from gasoline: historical and personal reflections. Environ Res 84(1):20–35. doi:10.1006/enrs.2000.4069

Needleman HL, Riess JA, Tobin MJ, Biesecker GE, Greenhouse JB (1996) Bone lead levels and delinquent behavior. JAMA 275(5):363–369. doi:10.1001/jama.1996.03530290033034
Nevin R (2000) How lead exposure relates to temporal changes in IQ, violent crime, and unwed pregnancy. Environ Res 83(1):1–22. doi:10.1006/enrs.1999.4045
NYSDCJS (2011) Crime in New York State 2011 final data. http://www.criminaljustice.ny.gov/pio/annualreport/nys-crime-report-2010.pdf
NYSDCJS (2014) Crime in New York State 2013 final data. http://www.criminaljustice.ny.gov/crimnet/ojsa/indexcrimes/nys-crime-report-2013.pdf
O'Brien RM (2000) Age period cohort characteristic models. Soc Sci Res 29(1):123–139. doi:10.1006/ssre.1999.0656
O'Brien RM (2014a) Estimable functions in age–period–cohort models: a unified approach. Qual Quant 48(1):457–474
O'Brien RM (2014b) Age–period–cohort models: approaches and analyses with aggregate data. Chapman and Hall/CRC, Boca Raton
O'Brien RM, Stockard J (2009) Can cohort replacement explain changes in the relationship between age and homicide offending? J Quant Criminol 25(1):79–101. doi:10.1007/s10940-008-9059-1
Pampel FC, Peters HE (1995) The Easterlin effect. Ann Rev Sociol 21:163–194. doi:10.2307/2083408
Porter LC, Bushway SD, Tsao HS, Smith HL (forthcoming). How the U.S. prison boom has changed the age distribution of the prison population. Criminology
Reyes J (2007) Environmental policy as social policy? The impact of childhood lead exposure on crime. BE J Econ Anal Policy. doi:10.2202/1935-1682.1796
Rodgers WL (1982) Estimable functions of age, period, and cohort Effects. Am Sociol Rev 47(6):774–787
Rosenfeld R, Fornango R (2014) The impact of police stops on precinct robbery and burglary rates in New York City, 2003–2010. Justice Q 31(1):96–122. doi:10.1080/07418825.2012.712152
Rosenfeld R, Messner SF (2009) The crime drop in comparative perspective: the impact of the economy and imprisonment on American and European burglary rates. Br J Sociol 60(3):445–471. doi:10.1111/j.1468-4446.2009.01251.x
Rosenfeld R, Oliver BE (2008) Evaluating recent changes in homicide and robbery rates. Justice Res Policy 10(2):49–65
Rosenfeld R, Fornango R, Rengifo AF (2007) The impact of order-maintenance policing on New York City homicide and robbery rates: 1988–2001. Criminology 45(2):355–384. doi:10.1111/j.1745-9125.2007.00081.x
Scheffé H (1959) The analysis of variance. John Wiley and Sons, Inc., New York
Searle SR (1971) Linear models. John Wiley and Sons, Inc., New York
Snyder HN (2012) Arrest in the United States, 1980–2009. (Report No. NCJ 234319). Retrieved from Bureau of Justice Statistics. http://www.bjs.gov/content/pub/pdf/aus8009.pdf
Steffensmeier D, Harer MD (1999) Making sense of recent U.S. crime trends, to 1996/1998: age composition effects and other explanations. J Res Crime Delinq 36(3):235–274. doi:10.1177/0022427899036003001
Steffensmeier DJ, Allan EA, Harer MD, Streifel C (1989) Age and the distribution of crime. Am J Sociol 94(4):803–831. doi:10.1086/229069
Stretesky PB, Lynch MJ (2001) The relationship between lead exposure and homicide. Arch Pediatr Adolesc Med 155(5):579–582. doi:10.1001/archpedi.155.5.579
Tarone RE, Chu KC (1996) Evaluation of birth cohort patterns in population disease rates. Am J Epidemiol 143(1):85–91
U.S. Census Bureau (2011) State population estimates, 1990–2010. http://www.census.gov/popest/data/historical/index.html
United States Department of Justice, Federal Bureau of Investigation (2011) Crime in the United States, 1990–2010. Prepared by the National Archive of Criminal Justice Data. http://www.ucrdatatool.gov
Weisburd D, Telep CW, Lawton BA (2014) Could innovations in policing have contributed to the New York City crime drop even in a period of declining police strength?: The case of stop, question and frisk as a hot spots policing strategy. Justice Q 31(1):129–153. doi:10.1080/07418825.2012.754920
Yang Y, Fu WJ, Land KC (2004) A methodological comparison of age–period–cohort models: the intrinsic estimator and conventional generalized linear models. Sociol Methodol 34(1):75–110
Yang Y, Schulhofer-Wohl S, Fu WJ, Land KC (2008) The intrinsic estimator for age–period–cohort analysis: what it is and how to use it1. Am J Sociol 113(6):1697–1736
Zimring FE (2007) The Great American crime decline. Oxford University Press, New York
Zimring FE (2011) The city that become safe: New York's lessons for urban crime and its control. Oxford University Press, New York